The Impact of Heterogeneity on Operator Performance in Futuristic Unmanned Vehicle Systems

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ABSTRACT

Recent studies have shown that with appropriate operator decision support and with sufficient automation, inverting the multiple operators to single-unmanned vehicle control paradigm is possible. These studies, however, have generally focused on homogeneous teams of vehicles, and have not completely addressed either the manifestation of heterogeneity in vehicle teams, or the effects of heterogeneity on operator capacity. An important implication of heterogeneity in unmanned vehicle teams is an increase in the diversity of possible team configurations available for each operator, as well as an increase in the diversity of possible attention allocation schemes that can be utilized by operators. To this end, this paper introduces a resource allocation framework that defines the strategies and processes that lead to alternate team configurations. The framework also highlights the sub-components of operator attention allocation schemes that can impact overall performance when supervising heterogeneous unmanned vehicle teams. Subsequently, a discrete event simulation model is presented as a means to model a single operator supervising multiple heterogeneous unmanned vehicles. Results from an experimental case study are then used to validate the model, and make predictions about operator performance for various heterogeneous team configurations.

1.0   INTRODUCTION

Increasing use of automation in unmanned vehicle (UV) systems has shifted the human operator's responsibility from manually controlling vehicles to managing vehicles at the supervisory control level. At the supervisory control level, implementation details of higher-level tasking initiated by the human is delegated to the automation onboard these vehicles (Sheridan 1992). The reduced workload afforded by supervisory control has several implications for unmanned system operations. One such ramification is an increase in operator idle time, which can be used as a force multiplier that allows operators to supervise multiple vehicles simultaneously, hence inverting the current many-to-one ratio of operators to vehicles. Inverting the operator to vehicle ratio can also be used to reduce manning in situations where the number of vehicles needed to accomplish missions exceeds that of available operators, which is currently a significant problem in the Predator community.

An increasing body of literature has examined the capacity of single operators to supervise multiple UVs (Ruff, Narayanan, and Draper 2002; Olsen and Wood 2003; Cummings et al. 2007). This research has mainly focused on the supervision of a homogeneous set of UVs. However, as unmanned vehicle system mission goals become increasingly demanding, the composition of UV teams is likely to involve vehicles of varying capabilities. For example, the military has proposed future operational concepts such as Network Centric Warfare (Alberts, Garstka, and Stein 1999) and the Future Combat System (FCS) (Feickert 2005) that require interoperability among UVs of varying attributes. In addition to heterogeneity across vehicle types, even a single UV can have multiple payloads. Thus, multiple mission objectives can drive heterogeneity in a system, which will ultimately lead to heterogeneity in operator tasks.

These multiple dimensions of heterogeneity introduce a number of problems in applying previous models of homogeneous UVs to the heterogeneous case. The different vehicle types that the team could be

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Recent studies have shown that with appropriate operator decision support and with sufficient automation, inverting the multiple operators to single-unmanned vehicle control paradigm is possible. These studies, however, have generally focused on homogeneous teams of vehicles, and have not completely addressed either the manifestation of heterogeneity in vehicle teams, or the effects of heterogeneity on operator capacity. An important implication of heterogeneity in unmanned vehicle teams is an increase in the diversity of possible team configurations available for each operator, as well as an increase in the diversity of possible attention allocation schemes that can be utilized by operators. To this end, this paper introduces a resource allocation framework that defines the strategies and processes that lead to alternate team configurations. The framework also highlights the sub-components of operator attention allocation schemes that can impact overall performance when supervising heterogeneous unmanned vehicle teams. Subsequently, a discrete event simulation model is presented as a means to model a single operator supervising multiple heterogeneous unmanned vehicles. Results from an experimental case study are then used to validate the model, and make predictions about operator performance for various heterogeneous team configurations.

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composed of and the different tasks that those vehicles could be assigned present a complex and mathematically intractable problem. Moreover, the method by which operators allocate their attention to the heterogeneous vehicles and/or tasks is likely to affect system performance. Finally, capturing the various operator management strategies and their effect on system performance is another important variable that must be considered.

This paper addresses these problems by introducing a framework that utilizes resource allocation to describe the process of heterogeneous UV team creation, as well as the attention allocation strategies that define the operator's interaction with the UV team. The paper then presents a discrete event simulation model that incorporates the framework's considerations. An experimental case study is then used to validate the ability of the model to predict the effects of changes in operator strategies and system design.

2.0 BACKGROUND

Previous research that examined the capacity of operators supervising multiple homogeneous robots by Olsen and Goodrich (2003) introduced several temporal-based metrics for describing operator interaction with unmanned vehicles. Neglect time (NT) was defined as the expected amount of time that a robot (which is representative of any UV) can be ignored before its performance drops below some acceptable threshold. Interaction time (IT) was defined as the average time it takes for a human to interact with the robot to ensure that it is still working toward mission accomplishment. In the single robot example (Figure 1(a)), the operator interacts with the robot for length of time IT and then ignores it for length of time NT, and then repeats this process after time NT by interacting with the robot once again. In the multiple robot case, an operator would interact with one robot at a time while neglecting all other robots (Figure 1(b)).

One drawback to this earlier work is the lack of accounting for human interaction delays and decision making inefficiencies. An additional critical variable needed when modeling human control of multiple vehicles is the concept of Wait Times (WT). Although it is possible for human beings to multi-task, humans act as serial processors in that they can only solve a single complex task at a time (Welford 1952; Broadbent 1958). While operators can rapidly switch between cognitive tasks, any sequence of tasks requiring complex cognition will form a queue and consequently, wait times will build (Cummings and Mitchell in press; Cummings et al. 2007). Wait times can occur when 1) a vehicle is neglected while the operator is busy interacting with another vehicle, or 2) when an operator requires re-orientation time while switching between vehicles, or 3) when a vehicle is neglected due to lack of operator situation awareness.
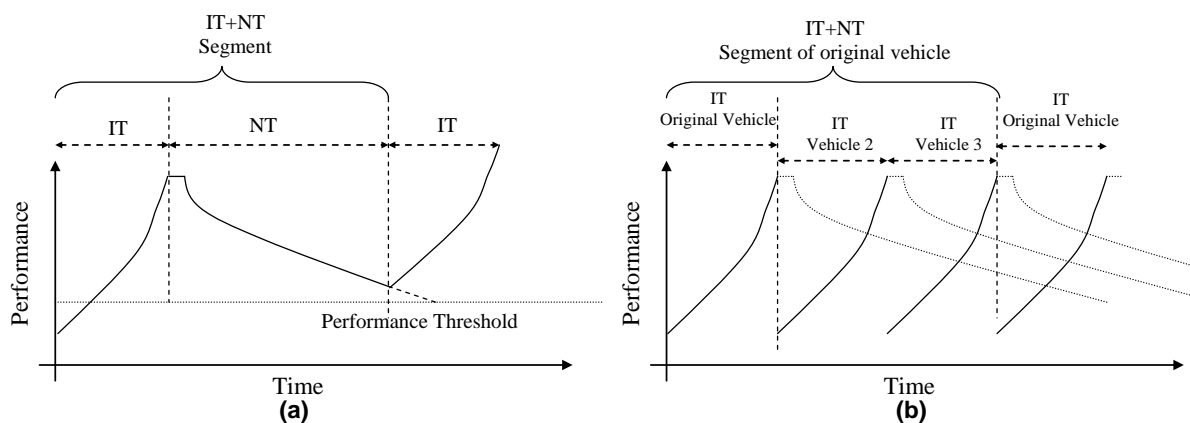

Figure 1. The relationship of NT and IT for (a) a single vehicle, and (b) multiple vehicles.

In order to model wait times, Cumming et al. (2007) proposed a queuing model of the human operator servicing multiple homogeneous UVs. In the single-server queuing network, the events that arrive are vehicles that require intervention to bring them above some performance threshold. This queuing model

forms the basis of the discrete event simulation described in subsequent sections that allowed us to model a single operator controlling multiple heterogeneous vehicles.

3.0 HETEROGENEITY FRAMEWORK

In order to develop better estimates of both human capacity for heterogeneous UV teams as well as the impact of varying mission tasks and vehicles on operator performance, we first created a framework that captures the processes by which UV teams are created and assigned to human operators.

Based on the idea of resource allocation, this framework is presented in Figure 2. The framework incorporates the allocation of three hierarchical resources: vehicles, human operators, and human attention. The first two resources, vehicles and human operators, are tangible physical assets that are allocated during mission planning, and it is through the allocation of these assets that vehicle teams are defined and assigned to operators. The third resource, operator attention, is an intangible asset whose allocation strategy defines the interaction of the operator with the team of UVs. This framework is not meant to be a detailed description of every aspect of UV assignment, but is instead meant to highlight the role of resource allocation strategies in influencing the effectiveness of human-vehicle/task interaction.
Starting from the top left of Figure 2, a vehicle allocation strategy is depicted as the method by which vehicles, based on their capabilities (which includes payloads, vehicle specifications, operational domain, and levels of automation) are assigned mission-based tasks that collectively satisfy mission objectives. The objective of the vehicle allocation strategy is to break down the mission objectives into tasks that can be allocated to the different vehicles. The choice of vehicle allocation strategies depends on the vehicle capabilities, the mission objectives, and the timing/control constraints imposed by the mission specification.

Next, a personnel allocation strategy is utilized in order to allocate an operator unit (at the organizational and individual level) to one or more mission task(s). The choice of personnel allocation strategies depends on the capabilities of the operators, as well as the interfaces available to them. Together, a vehicle allocation strategy and a personnel allocation strategy identify the particular vehicles and mission tasks that will be the responsibility of each operator unit. These initial two steps in the framework proposed in the preceding discussion are not the only possible format. It is possible for example to assign vehicles to personnel instead of assigning them to mission tasks. The main theme, however, across any allocation strategy combination is that vehicles, tasks, and personnel need to be assigned in order to define the vehicle/task team that each operator unit will be supervising.

The third and final strategy in the framework, the human-attention allocation strategy, is a function of the level at which the operator interacts with each vehicle/task, as well as the order by which the different vehicles/tasks are serviced. As depicted in Figure 2, operator resource allocation strategies are dependent on the operator-task assignment, the importance of the mission tasks, and the urgency of the mission tasks.

The significance of the overarching mission description block on the left hand side of Figure 2 represents the constraints imposed on the different strategies throughout the mission planning and re-planning phases. An example of this is a time on target (TOT) constraint that requires that an ISR (Intelligence, Surveillance and Reconnaissance) task be assigned to an unmanned aerial vehicle (UAV) over an unmanned undersea vehicle (UUV) due to the latter vehicle being unable to reach the area of interest in time.

The right hand side of Figure 2 represents the possible effects of the allocation strategies for all three resources on overall mission performance. For example, in a two-operator mission that requires the completion of two surface imagery tasks as well as two other target designation tasks, alternate personnel allocation strategies are possible. Assigning each operator two of the same tasks will likely result in different mission performance, as opposed to assigning each operator one of each task types.

The impact of alternate human-attention allocation strategies on overall mission performance is the subject of interest in this paper, and will be discussed further in the experiment section. First, a more detailed analysis of human-attention allocation is presented.

3.1 Attention Allocation Strategy

In supervising a UV mission, the operator's role is that of a mission manager whose task is to increase system performance in fulfilling that mission. The operator can interact with a UV when either a) the automation is not acting as expected and the operator believes that interaction can increase performance, or b) when an event occurs that requires human judgment and reasoning, something the automation is incapable of handling. For example, in the case of a UAV that is assigned a laser designation task, the operator could re-plan the vehicle path generated by automation in order to better meet a time-on-target restriction. The operator's judgment is also critical in deciding whether a specific target is the one that should be designated. When supervising multiple UVs, the operator attention allocation strategy will dictate the method by which the operator will supervise the different vehicles.

An overall attention allocation strategy can be dissected into three main components, which will be discussed in greater detail below: a) a neglect strategy, b) a complexity mitigation strategy, and c) a switching order strategy.

The neglect strategy affects the duration of time for which the operator neglects the UVs (i.e., the frequency by which the operator attends to the vehicles). The neglect strategy can vary per vehicle, and can be thought of as the scheme by which the operator distributes his/her attention across the different vehicles. A strategy where the operator services the vehicle only when necessary and otherwise allows the vehicle's automation to undertake tasks can be referred to as a neglect-macro-management strategy. On the other hand, a strategy where the operator constantly interferes with the vehicle's automation can be referred to as a neglect-micro-management strategy. Other neglect strategies can exist between these two extremes.

The second component of human behavior that influences attention allocation is the mitigation of system complexity through the use of cognitive abstractions. For example, operators can use mental abstractions to form vehicle groupings based on one or more criteria in order to reduce the complexity of supervising all the vehicles (Histon et al. 2002; Goodrich et al. 2007). Examples of criteria for grouping vehicles include the similarity of vehicle capabilities or task types. The result of such grouping abstractions is to organize the vehicles into relevant groups in order to simplify the task of managing them. For example, an operator that is supervising multiple UVs in a mission that includes coastal and inland surveillance might elect to divide the vehicles into two groups depending on their region of operation.

Finally, the third component of human-attention allocation is the order by which the different vehicles are serviced. When multiple vehicles require operator attention simultaneously, the operator must select the next vehicle to be serviced. Whereas this selection process is relatively simple in the homogeneous case, it is much more involved in the heterogeneous case. In the heterogeneous case, the difference in vehicles capabilities and their assigned tasks allows for more diverse selection strategies. For example, an operator that is supervising two UAVs with heterogeneous tasks can service the vehicles on a first come, first serve basis (FIFO) or allocate attention to the UAVs based on the priority of their tasks (preemptive priority queuing). The order by which the vehicles are serviced affects the total time that vehicles spend in the
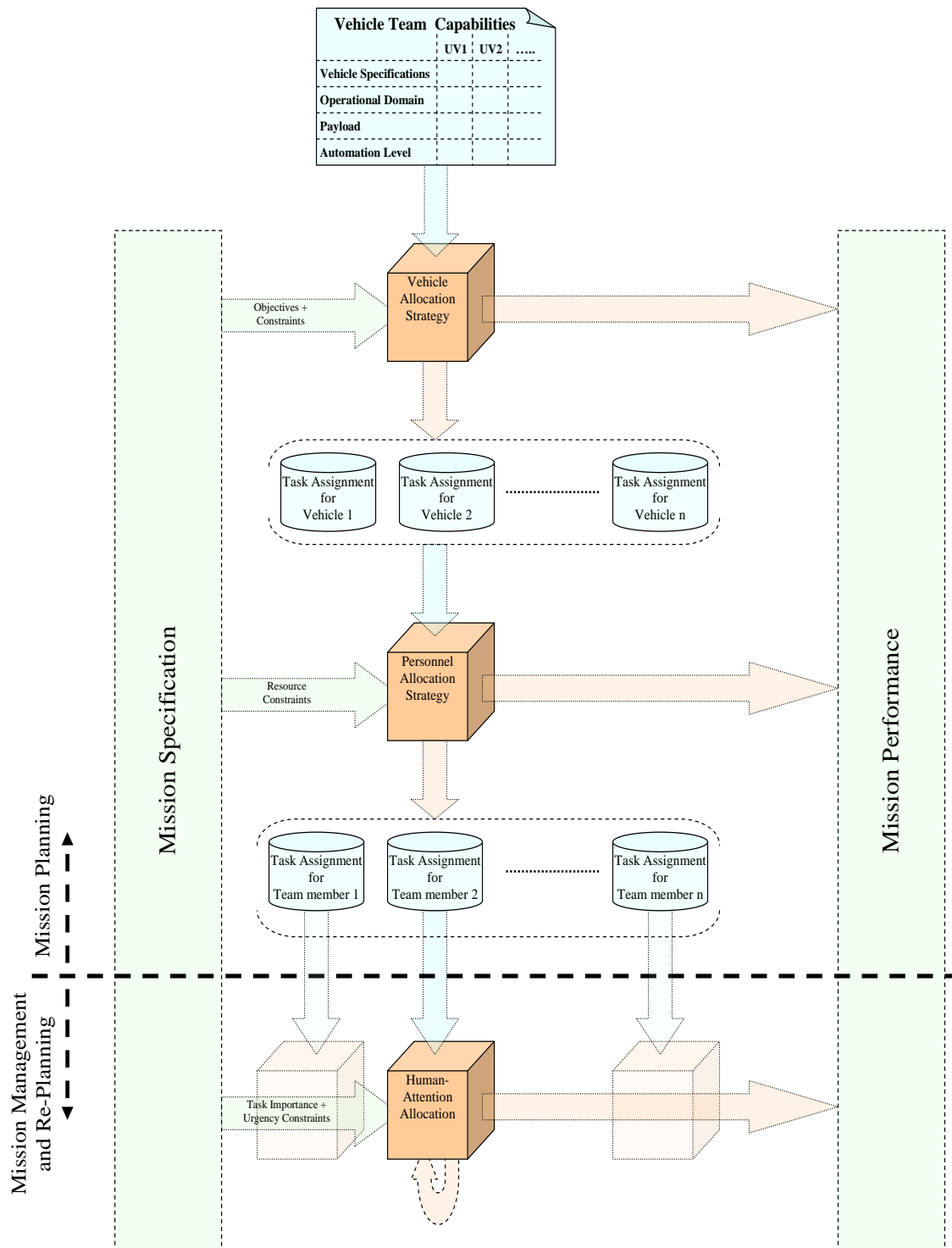
Figure 2. Human-Vehicle(s)/Task(s) Interaction Framework.

system, including the time they spend waiting for service as well as their processing time (Mau and Dolan 2006; Sheridan and Tulga 1978). In addition to having an effect on wait times, when a human operator switches between two different tasks, this is accompanied by a mental model switch that comes at a time

(or switch) cost (Goodrich, Quigley, and Cosenzo 2005; Squire, Trafton, and Parasuraman 2006). Thus switching between different combinations of heterogeneous vehicles can lead to different switch costs.

4.0 OPERATOR MODEL

To examine the impact of these various strategies on overall system performance, a discrete event simulation (DES) model of a heterogeneous UV system was developed. The DES model includes a) a queuing model of the human operator supervising multiple UVs, and b) a component to measure overall system performance, which will be discussed in the next section.

4.1 Overview

The operator model below was constructed under the assumption that the operator is acting in a supervisory control mode and that the different vehicles in the team are highly autonomous. Therefore, the vehicles generally only require operator interaction for tasks that require human judgment and reasoning. The operator can, however, attend to a vehicle even if the vehicle has not generated a task that requires human judgment and reasoning by initiating a re-plan that could potentially lead to improved performance. The operator model is based on the single server queue with multiple input streams (Figure 3). An event in this queuing model represents tasks to be attended to by the operator. The operator can attend to only one event at a time, and this is captured by the single-server architecture such that any events that arrive while the operator is busy will wait in a queue. There are two main event types that are included in the model; a) events generated by the vehicles due to the emergence of tasks that require human judgment and reasoning, and b) events that the operator induces by deciding to re-plan a vehicle's existing plan (this is normally done because the operator believes he/she can improve some metric as a result of the re-planning). The separate input streams corresponding to each of the vehicles in the team allow for distinct arrival and service distributions for each vehicle, a property required to model a heterogeneous UV team.
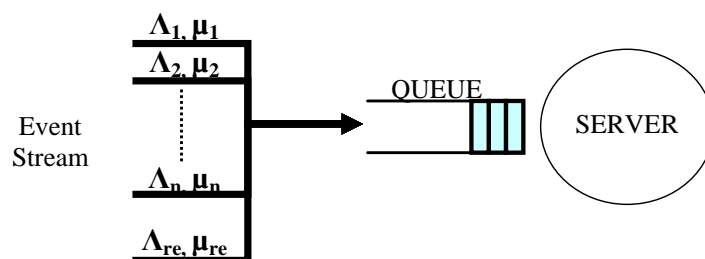

Figure 3. Human-Vehicle(s)/Task(s) Interaction Framework.

4.2 Vehicle-Generated Events

There is one input stream associated with each of the UVs in the team (1 to n). An event arrives to the system if the vehicle associated with the stream generates a task that requires operator judgment/reasoning and the operator notices the vehicle's request. A vehicle that has already generated an event must wait for operator attention before it can continue its mission and generate another event. An event is therefore generated for a particular stream only if an event corresponding to that stream does not already exist in the system. Thus inter-arrival times for a stream are the times between the completion of service for an event and the arrival of the next event. The inter-arrival times for events from the vehicle associated with stream i is a random variable (Λ_i) which has a particular probability distribution. The distribution of Λ_i is a function of two main components; a) the distribution of the random variable that describes the time following a service that it takes a vehicle to generate a task that requires operator judgment/reasoning and, b) operator loss of situational awareness (Equation 1).

$$\Lambda_i = X_i + \chi * X_i \qquad (1)$$

The first term in Equation 1, X_i, is a random variable that describes the time between a service completion for a task that requires operator judgment and reasoning and the generation of the of the next such task. The probability distribution describing X_i is a function of the vehicle's level of automation, the task complexity, and the environment of operation. The generation of a task does not necessarily imply that the operator notices the generated task as the rate excludes any effects due to loss of situational awareness (SA).

The second term in Equation 1, $\chi*X_i$, represents a penalty due to operator loss of situational awareness (SA), with χ taking a value of zero when the operator has complete SA and higher χ indicating degraded SA. SA is defined as the combination of perception of elements in the environment, the comprehension of their meaning, and the projection of the their status in the future (Endlsey 1995). The effect of low SA (i.e., high χ) is to create additional vehicle wait time (WTSA) which increases Λ, due to the operator taking longer to notice the vehicle (Cummings et al. 2007). In order to capture SA, this model builds on an assumption that SA is related to operator utilization (Endsley 1993). When operators are under high levels of utilization, it is assumed that they are too busy to accumulate the information that is required to build SA. At the same time, when operators are under-utilized, it is presumed that due to a low level of arousal and complacency, they could overlook information from the environment, which would also lead to low SA.
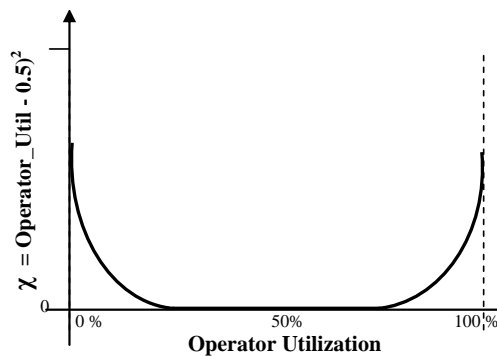

Figure 4. χ curve

In the DES, the χ variable in Equation 1 is related to operator utilization through a parabolic function that is concave upwards (Figure 4). This implies that at both high and low operator utilization, χ increases according to a quadratic law and therefore increases Λ correspondingly. The parabolic relationship is inspired by the Yerkes Dodson Law (Yerkes and Dodson 1908), which relates operator utilization to performance. The χ variable is multiplied by X in order to capture the effect on Λ due to loss of SA, which is a function of the rate at which the vehicle generates tasks that require operator intervention. Vehicles that produce tasks infrequently are serviced less often, and are therefore more likely to be overlooked than vehicles that are serviced more frequently.

Also associated with each input stream is a service rate which is based on the length of time it takes the operator to interact with a particular vehicle, corresponding to the arriving event. The service rate of events, which is a random variable, is modeled using a service rate distribution (μ_i), which is a function of two main components; a) the distribution of the rate at which operators can service tasks associated with vehicle *i*, and b) wait times due to context switching (Equation 2).

$$\mu_i = Y_i + (\varphi + \tau) * Y_i \qquad (2)$$

The first term in Equation 2, Y_i, is the random variable that describes the length of time for which the operator must interact with vehicle i in order to address tasks that require operator judgment and reasoning. The probability distribution describing Y_i is mainly a function of interface and decision support quality. The second term in Equation 2 is a function of the context switching times that arise when servicing a specific vehicle. φ is a coefficient for calculating the time penalty due to switching between vehicles with heterogeneous capabilities, and τ is a coefficient for calculating the time penalty due to switching between vehicles with heterogeneous tasks. The switch cost is not limited to switching between cognitively complex tasks, but exists even when humans switch between cognitively simple ones (Rogers and Monsell 1995). For example, Goodrich et al. (2005) demonstrated that the existence of context switching costs in multi-vehicle control is unavoidable, and that the amount of time required to switch between vehicles can be substantial. For this DES model, context switching was accounted for whenever the current vehicle's capability or its task type differed from that of the last vehicle serviced (these effects are captured by the φ and τ variables respectively). The effect of switching times creates additional interaction wait times (WTI) which increases μ, due to the operator taking longer to interact with the vehicle. The $(\varphi + \tau)$ factor is multiplied by Y in order to capture the fact that the context switching time effect on μ is a function of the vehicle's interaction time.

4.3 Operator Neglect Strategy (Operator-Induced Events)

In addition to a stream corresponding to each of the vehicles, there is one additional stream for operator-induced events that the operator creates by deciding to re-plan a vehicle's existing plan. Although vehicles only generate events corresponding to tasks that require operator judgment/reasoning, the operator can also interrupt a vehicle if he/she believes they can improve some system performance as a result of re-planning. The arrival rate of events for this stream is based on a distribution of the rate at which the operator wishes to re-plan (Λ_{re}). This distribution represents the operator neglect strategy. For example, an aggressive rate of re-planning would result in a neglect micro-management strategy, and a strategy comprised of less frequent re-plans would result in a neglect macro-management strategy. Also associated with each operator-induced event is a service rate (μ_{re}) that describes how long it takes the operator to complete a re-planning.

5.0 PERFORMANCE METRIC

The model just described allows for the manipulation of team heterogeneity as well as the strategies utilized by operators in allocating their attention. In order to evaluate the effectiveness of alternate strategies while supervising teams with different levels of heterogeneity, a system performance metric was developed. For this research effort, we developed a cost performance model that captures system performance, but also ensures a heavy penalty when individual vehicle performance falls below a certain threshold. This performance metric measures different variables from the operator model in order to evaluate system performance (Equation 3).

$$Performance = \frac{1}{\sum_i priority_i} \sum_i \left(priority_i \bullet P_i \bullet \min(1, \Lambda_i) \right) \qquad (3)$$

Each UV's contribution to the performance metric is captured through one term in Equation 3. The P_i factor in each term represents the quality of the operator's interaction with that vehicle. The MIN(1, Δ_i) factor represents the timeliness of the operator's interaction, and therefore ensures that the value added due to the operator's interaction is weighted by the punctuality of that interaction. The metric therefore reflects both the timeliness of interaction as well as the quality of interaction. Finally, each term in the equation is weighted by the priority of that vehicle, which is dependent on the value of that vehicle's task

as a proportion of the overall mission objective. These priorities can also be predefined during mission planning and might be dictated by rules of engagement. Mission performance is therefore most sensitive to those assigned tasks with significant contribution to the mission objective. A vehicle that underperforms on an individual basis will negatively impact the performance metric, and at the same time, the metric measures the total contribution of all vehicles which serves as an overall mission performance indicator.

One important factor that influences both operator and mission performance is the quality of the human-computer interface and associated decision support. By comparing performance resulting from alternate strategies, a conclusion can be made as to what strategies promote the best performance trends. This can encourage system designers to design interfaces that amplify these strategies and mute those that result in less effective performance. A study was therefore conducted to provide as a preliminary investigation of the effects of alternate resource allocation strategies on system performance.

6.0 EXPERIMENTAL CASE STUDY

To evaluate the ability of the model to accurately predict the performance characteristics of human-UV teams, predictions from the model were compared to results from an experimental study conducted to investigate operator performance issues in the control of multiple simulated UVs conducting a simulated search-and-rescue mission. The experimental study and model parameters are discussed below.

6.1 Software Test-bed

Various aspects of the software test-bed used in the user study are described in this subsection, which include *mission*, *interface*, and *UV behavior*.

Mission. The human-UV team (which consisted of the participant and multiple simulated UVs) was assigned the task of removing as many objects as possible from the maze in an 8-minute time period. The objects were randomly spread through the maze, which was initially unknown. However, as each UV moved about the maze, it created a map which it shared with the participant and the other UVs in the team. The team could only see the positions of six of the objects initially. In each minute of the session, the locations of two additional objects were shown. Thus, there were 22 possible objects to collect during a session.

An object was removed from the maze (i.e., collected) using a three-step process. First, a UV moved to the location of the object in the maze (i.e., target designation, mission planning, path planning, and UV monitoring). Second, the UV "picked up" the object (i.e., sensor analysis and scanning). In the real world, performing such an action might require the human operator to assist in identifying the object with video or laser data. To simulate this task, we asked users to identify a city on a map of the mainland United States using *Google Earth*-style software. Third, the UV carried the object out of the maze via one of two exits.

Interface. The human-UV interface was the two-screen display shown in Figure 5. On the left screen, the map of the maze was displayed, along with the positions of the UVs and (known) objects in the maze. The right screen was used to locate the cities. A participant could only control one UV at a time. When a user desired to control a certain UV, s(he) clicked a button on the interface corresponding to that UV (labeled UV1, UV2, etc.). Once the participant selected the UV, he/she could direct the UV by designating a goal location and modifying the UV's intended path to that goal. Designating a goal for the UV was done by dragging the goal icon corresponding to the UV in question to the desired location. Once the UV received a goal command, it generated and displayed the path it intended to follow. The participant was allowed to modify this path using the mouse.

UV Behavior. The UVs' map of the maze took the form of an undirected graph. Each edge of the graph was an ordered pair (u, v) representing a connection between vertices u and v in the graph. Associated with each edge was a weight indicating the cost for a UV to move along that edge. Since the maze was not fully known, a UV had to choose between (a) moving along the shortest path of the known maze to its user-specified goal and (b) exploring the unknown portions of the maze in hopes of finding a shorter path. To make this decision, a UV assumed that an unmapped edge from a known vertex v led directly to the goal position with a cost equal to the Manhattan distance from v to the UV's goal, plus some cost of exploration (C_E). Each UV used Dijkstra's algorithm on the resulting graph to determine the path it intended to follow.
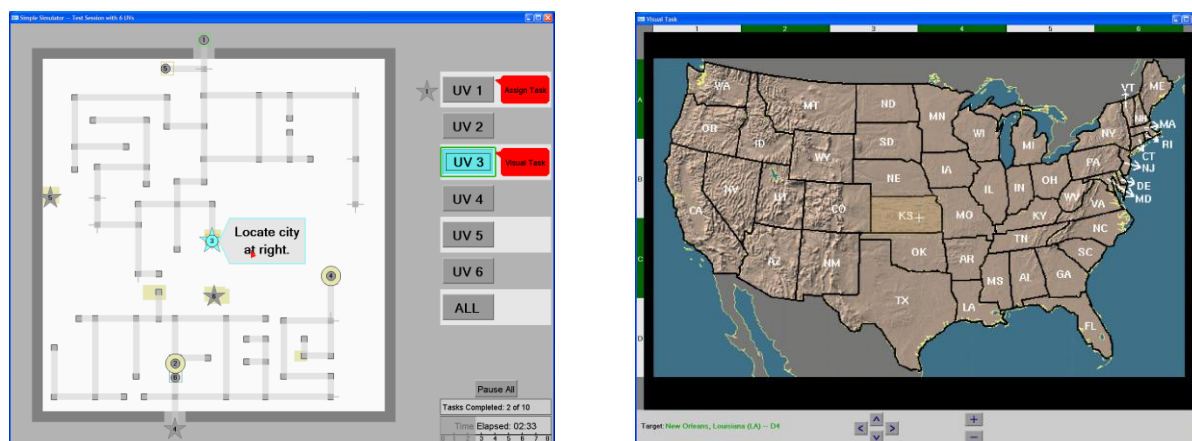

Figure 5. Two-screen interface by which an operator directed the UVs.

Using this approach, the constant C_E determines the degree to which the UVs explore the unknown maze. Higher values of C_E result in less exploration. We used a small value of C_E for a UV that was searching for an object, and a higher value for a UV that was carrying an object. Since users sometimes felt that the resulting behavior was undesirable, they were allowed to modify a UV's path if they desired.

Two different versions of UV autonomy were employed in the user study. In the first condition, called the *no-decision support* (NDS) condition, each UV's goal destination was determined completely by the human operator. Once the UV arrived at its user-defined goal destination, it did not move again until it received a new command from the user.

In the second condition, called the *full-decision support* (FDS) condition, each UV automatically selected a new goal when it was left idle. Specifically, a management-by-exception level of automation was used in which a UV left idle at its goal destination, but not on an object in the maze, waited 15 seconds for the user to intervene. If the user did not intervene, the UV automatically moved to the nearest unassigned object (if the UV was searching for an object) or the nearest exit (if the UV was already carrying an object). Additionally, if the user did not intervene, UVs automatically chose to exit the maze via the (estimated) nearest exit in the final 45 seconds of a session. The FDS condition also had one other additional decision support tool to assist the user in locating cities on the map (to "pick up" objects). This decision support tool decreased the search time for a city on the map by about 5 seconds on average.

6.2 Experimental Procedure

The experimental design was a 2x4 factor study. The decision support conditions (NDS or FDS) was a between subjects factor. UV team size was a within subjects factor; each participant performed the search-and-rescue mission for team sizes of two, four, six, and eight UVs. The order in which the

participants used each team size was counter-balanced throughout the study. Each participant was first randomly assigned to a decision support condition (NDS or FDS), and then was trained on all aspects of the system. They then completed three comprehensive practice sessions. Following these practice sessions, each participant performed four test sessions (each with a different team size). Participants were paid $10 per hour; the highest scorer also received a $100 gift certificate. Thirty-two participants between the ages of 18 and 45 (mean 24.4 years old) participated in the study, 16 in each condition.

6.3 Model Parameters

In order to compare the DES model results to the human-on-the-loop experimental results, vehicle-generated and operator-induced distributions in the case study were identified. Vehicle-generated events include both locating a city on the map and goal assignment in the case of the NDS condition, but only locating a city on the map in the FDS condition (since the UV could function without goal-assignments from the user in this condition). Thus, five data sets were measured from the experimental data: 1) arrival rate of vehicle-generated events after the UV was serviced for a vehicle-generated event; 2) arrival rate of vehicle-generated events after the UV was serviced for an operator-induced event, 3) service times of vehicle-generated events, 4) arrival rate of operator-induced events, and 5) service times of operator-induced events.

The data sets collected were then used to generate random distributions that were used by the model. In most cases, the distribution that best fit the data was the lognormal distribution. This was expected for both service times and arrival rates since they are skewed to the left, corresponding to the cases where an abnormally long amount of time passes between events or while the operating is servicing a vehicle. The measured service times and arrival rates for vehicle-generated and operator induced tasks are summarized in Appendix A1.

The complete model of the human-UV team also requires a performance model. In the user study, the team scored points when an object was removed from the maze. In the NDS condition, this required two vehicle-generated events to occur (goal-assignment and locating a city). Thus, the DES Model awarded a point for the servicing of every two vehicle-generated events. In the FDS condition, only one vehicle-generated event (locating a city) needed to be performed. Thus, in this condition, the DES Model awarded a point for every serviced vehicle-generated event.

7.0 RESULTS & DISCUSSION

In this section, predictions made by the model for system performance (number of objects collected) and operator utilization (percent operator busy time) are compared to observed results from the user study. Operator utilization is included in the analysis since users who are more than 70% busy typically demonstrate degraded performance (Schmidt 1978; Rouse 1983; Cummings and Guerlain 2007). After these predictions are analyzed and discussed, predictions made by the model for heterogeneous teams are also presented and discussed.

7.1 Homogeneous Teams

Using the distributions of arrival rates and service times generated from the data in the user study, 10,000 trials were conducted with the discrete event simulator to predict system performance and operator utilization for each condition of the study.

The observed system performance and operator utilization from the user study are compared with the model's estimates in Figures 6 and 7, respectively. For the FDS condition, the model's predictions for system performance are all within the 95% confidence intervals. Likewise, the FDS utilization predictions are all within the 95% confidence intervals except in the 2-UV case. In this case, the model underestimates operator utilization by approximately one standard deviation. In the NDS condition, the model's

predictions of system performance are within the 95% confidence intervals for the 4- and 6-UV conditions, but were low (1.6 standard deviations away from the mean) in the 2-UV condition and slightly high in the 8-UV condition (0.6 standard deviations from the mean). Additionally, predictions of operator utilization are within the 95% confidence intervals for 6- and 8-UV teams, but not the 2- and 4-UV teams, where predictions are off by 2 and 0.8 standard deviations respectively.
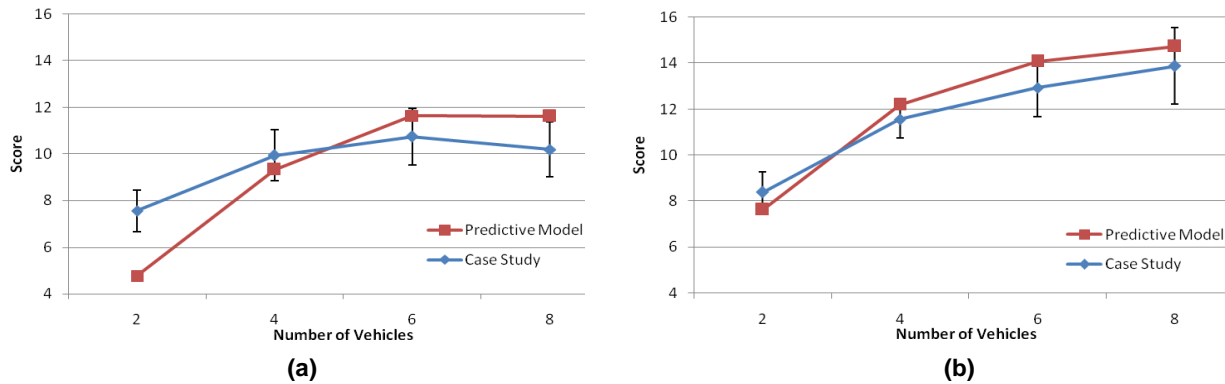

Figure 6. Comparison of mean performance scores from predictive model and case study for 2, 4, 6, and 8 vehicles for (a) the no decision support case, and (b) the full decision support case.

Two observations about the accuracy of the model's predictions can be made from these results. First, predictions are more accurate for larger teams than small teams. This trend appears to be caused at least to some degree by overly high penalties associated with low utilization in the SA model (Equation 1 and Figure 4). As a result, the human is modeled as not servicing UVs as often as necessary in the 2-UV condition. This leads to the low predictions for both operator utilization and system performance in this condition.

The second trend observed in Figures 6 and 7 is that the model's estimates are better in the FDS condition than in the NDS condition. Again, it appears that this trend is due to difficulties in modeling human behavior, as human behavior is more difficult to model than is automation. Thus, systems that rely more on human behavior (i.e., the NDS condition) are more difficult to accurately model than systems that rely more on automated behavior (i.e., the FDS condition).

Despite variations in the accuracy of the model's predictions, the predictions do capture the general trends in system performance and operator utilization as the size of the team and the level of decision support change. This result is important since it means that the model gives adequate predictions of the behavior of different system architectures in a cost effective manner. Given this positive result, the model is now used to predict system performance and operator utilization in the same mission for heterogeneous teams.

7.2 Heterogeneous Teams

The teams considered in the user study consisted of UVs with homogeneous capabilities. In this subsection, simulated heterogeneous UV teams of sizes 2, 4, 6, and 8 with NDS and FDS capabilities are considered. Such teams reflect situations in which operators must simultaneously supervise both legacy UVs with less autonomy (such as NDS) and newer, more automated UVs (such as FDS). The performance of each of these teams using various operator strategies is compared to the performance of the homogeneous teams. Different switching strategies and neglect strategies are considered.

Switching Strategies. Recall that switching strategies refer to the order in which the operator attends to UVs that need to be serviced. This requires that UVs and tasks be given specific priorities, and that the operator services the UV with the highest priority. For the heterogeneous model predictions, a first-in-first-out (FIFO) switching scheme as well as two different priority schemes are considered. In the first priority scheme (referred to as *NDS-preferred*), vehicle-generated events by UVs with NDS capabilities are given the highest priority, followed by vehicle-generated events by UVs with FDS capabilities, followed by operator-induced events. For the second priority scheme (referred to as *FDS-preferred*), the highest priority is given to vehicle-generated events from UVs with FDS capabilities, followed by vehicle-generated events by UVs with NDS capabilities, followed by operator-induced events.

In Figure 8, the performance scores and utilizations of the heterogeneous teams for each of the three switching strategies are compared to the results associated with the two homogeneous teams from the previous section. Due to the congruity of the vehicles, it can be assumed that operators exhibited a FIFO switching strategy in the two homogeneous cases. Figure 8(a) shows that all three heterogeneous team results have nearly identical performance scores that fall in between the performances of the NDS and FDS homogeneous teams. For teams of sizes 6 and 8, operator utilization is saturated in the heterogeneous case for all three switching strategies, just like in the homogeneous FDS case (Figure 8(b)). However, performance for the homogeneous FDS case exceeds the performance in the heterogeneous cases. This is expected since the heterogeneous operators have a higher task load due to the inclusion of NDS vehicles in the teams, which require more regular operator attention. In the homogeneous FDS case, operators take advantage of the reduced task load by doing extra re-planning, which results in improved performance.
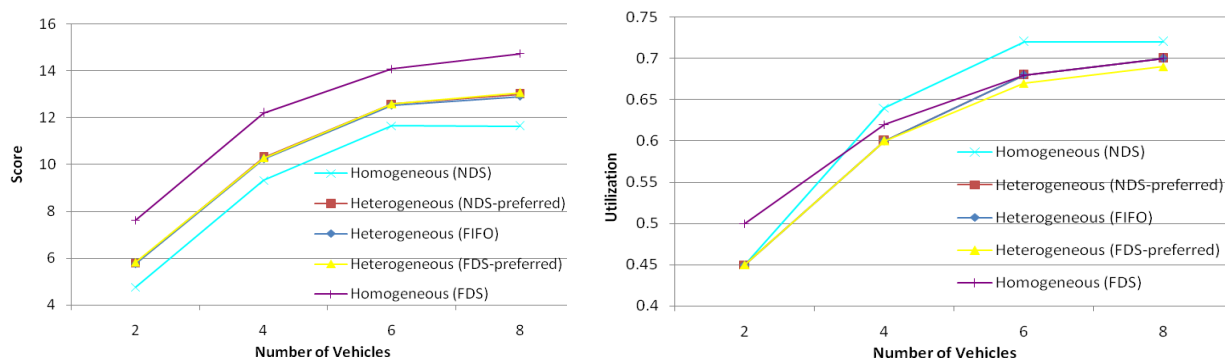

Figure 8. Comparison of (a) mean performance scores, and (b) mean utilizations when using alternate switching strategies for teams with 2, 4, 6, and 8 vehicles.

Thus our model predicts that vehicle team size and the level of decision support will have a more profound impact on system performance for this particular search-and-rescue mission than does the operator's choice of switching strategy. For this simulated mission, the system was relatively robust in terms of operator strategy, which should be a design goal in human supervisory control systems. Because military operators receive significant on-the-job training and experience high turnover rates, a well-designed system that can tolerate wide variability in strategies is crucial for future multiple-UV systems.

Neglect Strategies. Recall that an operator's neglect strategy refers to how likely she/he is to re-program a UV at any point in time. In the heterogeneous case, it can be important to use different neglect strategies for different UV systems. For example, a highly autonomous UV may need to be re-planned at a different rate than a less autonomous UV.

For the heterogeneous model predictions, three neglect strategies are analyzed. In the first strategy (referred to as *50/50*), the operator applies an equal neglect strategy to UVs with NDS and FDS

capabilities. In the second strategy (called *Re-plan NDS*), the operator chooses to re-plan UVs with NDS capabilities, but not UVs with FDS capabilities. In the third strategy (called *Re-plan FDS*), the operator re-plans UVs with FDS capabilities, but not UVs with NDS capabilities.

The system performance and operator utilization of these teams with the three operator strategies are compared to NDS and FDS homogeneous teams in Figure 9. Figure 9(a) shows that as with the previous predictions, the homogeneous team operators with full decision support achieved the highest performance due to the lower task and mission complexity. In addition, those heterogeneous operators that focused on replanning with no decision support performed at the same degraded level as those operators with a homogeneous team with no decision support. Interestingly, these same operators experienced the lowest utilization, so they had spare cognitive resources but performed at a degraded level because they did not efficiently allocate their attention. These results illustrate the need to provide decision support, regardless of the team composition, as well as directed decision support that makes it clear to the operator what tasks are the most critical.

Another interesting result is that when operators re-plan UVs with FDS capabilities (i.e., in *50/50* and *Re-plan FDS*), the performance of the team improves. These results imply that when transitioning from legacy non-highly autonomous vehicles to more autonomous vehicles, operators supervising mixed teams can achieve higher levels of performance, but that they need to understand when and how to override the automation when replanning.
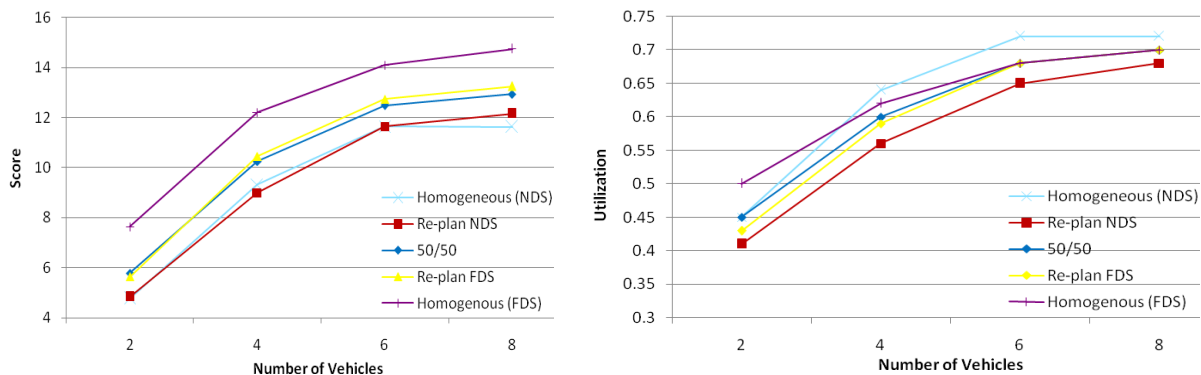

Figure 9. Comparison of (a) mean performance scores, and (b) mean utilizations when using alternate neglect strategies for teams with 2, 4, 6, and 8 vehicles.

8.0 CONCLUSIONS

A framework was presented that identified the resource allocation strategies that are fundamental in defining the types of heterogeneity that will be present in vehicle teams, as well as the different attention allocation strategies that are available to the human operator in supervising such teams. Based on this framework, a discrete-event simulation model was developed to investigate the effect of alternate operator strategies and team compositions in supervising multiple heterogeneous unmanned vehicles. In this paper, the model was used to predict the system performance and operator utilization of multiple simulated homogeneous UV teams. Comparisons of these predictions with observed human-in-the-loop experimental results show that the model adequately captures these system dynamics for these homogeneous cases.

Because this model allows for alternative configurations both in vehicle assignments and in operator strategies, it is useful for modeling other system configurations. In this paper, predictions were made for heterogeneous teams of different sizes and capabilities, and were compared to the performance scores and utilizations obtained in the user study for homogeneous teams. The performance in the heterogeneous

cases was bounded by the results obtained with homogenous teams, demonstrating that this simulated search and rescue human-robot system was relatively robust to changes in operator strategies, but that the presence and correct use of the automated decision support in heterogeneous UV teams is critical. While these results are encouraging, the model must still be validated for heterogeneous teams in future work.

9.0 ACKNOWLEDGEMENTS

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11.0 APPENDIX

A1: Summary of case study results for the no decision support trials

	# of Vehicles	Events	Re-Planning	Service Time	Arrival Rates	Decision Support
Mean	2	OI	78.51 s	7.17714 s	60.84 s	ND
Distribution	2	OI	Lognormal	Lognormal	Lognormal	ND
Parameters	2	OI	σ=1.1871 μ=3.6762	σ=0.83977 μ=1.6274	σ=1.0759 μ=3.5615	ND
Mean	2	VG	67.25 s	16.747 s		ND
Distribution	2	VG	Gamma	Exponential		ND
Parameters	2	VG	α=0.4444 β=151.3	λ=0.05971		ND
Mean	2	OI	70.08 s	5.645 s	25.187 s	F
Distribution	2	OI	Lognormal	Lognormal	Exponential	F
Parameters	2	OI	σ=1.2099 μ=3.550	σ=0.76877 μ=1.4283	λ=0.0397	F
Mean	2	VG	86.48 s	22.79 s		F
Distribution	2	VG	Lognormal	Lognormal		F
Parameters	2	VG	σ=0.5138 μ=4.307	σ=0.4093 μ=3.026		F
Mean	4	OI	45.55 s	4.9 s	77.31 s	ND
Distribution	4	OI	Lognormal	Lognormal	Lognormal	ND
Parameters	4	OI	σ=0.9985β μ=3.246	σ=0.7005 μ=1.312	σ=1.234 μ=3.685	ND
Mean	4	VG	54.26 s	14.2037 s		ND
Distribution	4	VG	Lognormal	Gamma		ND
Parameters	4	VG	σ=1.130 μ=3.351	σ=0.66218 μ=1.2805		ND
Mean	4	OI	72.87 s	4.509 s	70.08 s	F
Distribution	4	OI	Lognormal	Lognormal	Lognormal	F
Parameters	4	OI	σ=1.2244 μ=3.6333	σ=0.76877 μ=1.4283	σ=1.201 μ=3.550	F
Mean	4	VG	107.93 s	19.76 s		F
Distribution	4	VG	Lognormal	Lognormal		F
Parameters	4	VG	σ=0.637 μ=4.4525	σ=0.37596 μ=2.8978		F
Mean	6	OI	51.06 s	5.724 s	81.71 s	ND
Distribution	6	OI	Lognormal	Lognormal	Lognormal	ND
Parameters	6	OI	σ=1.0456 μ=3.3778	σ=0.73413 μ=1.4213	σ=1.328 μ=3.6353	ND
Mean	6	VG	58.93 s	12.57 s		ND
Distribution	6	VG	Lognormal	Gamma		ND
Parameters	6	VG	σ=1.1743 μ=3.4169	α=0.94565 β=13.292		ND
Mean	6	OI	82.83s	4.331 s	23.90253 s	F
Distribution	6	OI	Lognormal	Lognormal	Lognormal	F
Parameters	6	OI	σ=1.2356 μ=3.7949	σ=0.63637 μ=1.2603	σ=1.2272 μ=2.4277	F
Mean	6	VG	103.616 s	19.81 s		F
Distribution	6	VG	Lognormal	Lognormal		F
Parameters	6	VG	σ=0.53908 μ=4.4863	σ=0.37706 μ=2.9057		F
Mean	8	OI	60.56 s	4.558 s	76.44 s	ND
Distribution	8	OI	Lognormal	Lognormal	Gamma	ND
Parameters	8	OI	σ=1.175 μ=3.3932	σ=0.62325 μ=1.3214	α=0.60371 β=126.63	ND
Mean	8	VG	67.25 s	12.56 s		ND
Distribution	8	VG	Gamma	Lognormal		ND
Parameters	8	VG	α=0.4444 β=151.3	σ=1.0852 μ=1.9596		ND
Mean	8	OI	91.68 s	4.111 s	28.45 s	F
Distribution	8	OI	Lognormal	Lognormal	Lognormal	F
Parameters	8	OI	σ=1.2261 μ=3.9041	σ=0.59295 μ=1.2155	σ=1.3543 μ=2.3909	F
Mean	8	VG	113.8 s	20.62s		F
Distribution	8	VG	Lognormal	Lognormal		F
Parameters	8	VG	σ=0.54382 μ=4.5835	σ=0.40095 μ=2.9132		F

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